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Technical paper

An intelligent monitoring system for robotic milling process based on transfer learning and digital twin

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ABSTRACT

Robotic milling is becoming widely used in aerospace and auto manufacturing due to its high flexibility and strong adaptability. However, the practical challenges including complex and time-consuming robot trajectory planning, insufficient monitoring, and lacking three-dimensional visualization limits its further application. To address these challenges, an intelligent monitoring system for robotic milling process based on transfer learning and digital twin was proposed and developed in this paper. Firstly, the fundamental framework of this system was conducted based on a five-dimensional digital twin model for motion simulation, visualization, and tool wear prediction during the robotic milling process. Secondly, the parsing algorithm converting NC code to robot's machining trajectory and material removal algorithm based on bounding box and mesh deformation were proposed for robotic dynamic milling simulation. Thirdly, a novel transfer learning algorithm named CNN-LSTM-TrAdaBoost.R2 was developed by integrating CNN-LSTM with TrAdaBoost.R2 for automated feature extraction and real-time prediction of tool wear. Finally, the effective and accuracy of tool wear prediction algorithm is verified by ablation experiment and the robotic milling simulation is validated by real milling experiment, as well. The results indicate that the proposed monitoring system for robotic milling process demonstrates great virtual-real mapping. It can offer new insights and technical support for constructing sophisticated digital twin frameworks and enhancing operational monitoring in manufacturing systems.

1. Introduction

In the context of intelligent manufacturing, robots serve as representative equipment embodying automation, intelligence, and digitization, playing a crucial role in various manufacturing sectors [1]. In material milling, robots exhibit significant advantages due to their high flexibility, multiple degrees of freedom, and broad adaptability, particularly in scenarios involving complex shapes, small batch sizes, and moderate precision requirements [2,3]. However, practical challenges persist, as robot machining trajectory planning remains time-consuming and poses safety risks, while achieving effective three-dimensional visualization of the milling process and real-time prediction of cutting tool wear continues to be problematic.

The technologies for robotic monitoring include Prognostics and Health Management (PHM), bilateral teleoperation, and digital twin technology. PHM involves the development of mathematical models for the robot to detect and analyze its health status, thereby predicting potential failures [4]. Bilateral teleoperation enables real-time interaction between the master and slave systems, allowing for precise remote control of the robot [5,6]. Digital twin technology creates a digital replica of the physical environment, enabling highly realistic representations through synchronization between the digital and physical spaces [7,8]. This characteristic of digital twin technology allows for the accurate reflection of an object's behavior in virtual space with a corresponding scale [9], overcoming the non-intuitive presentation effects associated with PHM and avoiding the dependence on physical devices inherent in bilateral teleoperation. Furthermore, digital twin technology is increasingly being integrated with PHM and bilateral teleoperation to offer new solutions for robotic monitoring [10,11].

The concept of digital twin was extended by Professor Tao, who proposed a five-dimensional model based on digital twin [12]. In this study, we propose establishing a five-dimensional model for robotic milling environments using digital twin technology. This facilitates simulation testing, parameter adjustments, motion planning, and other operations in a virtual environment. The results are subsequently fed back to the physical system, thereby enhancing both performance and stability [13,14]. Additionally, the collection and analysis of extensive data generated during robotic operations through digital twin enable fault diagnosis, preventive maintenance, and life cycle assessment,

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thereby supporting improved efficiency and resilience [15]. This introduces several challenges in both the design and implementation of solutions. The sensors generate multimodal data, requiring the integration and analysis of these diverse data streams to create a comprehensive and unified representation. The digital twin model is connected to the physical environment via communication, making it essential to establish a reliable communication process to ensure real-time interaction. The simulation of the machining process depends on the real-time evolution of the model, which requires sufficient precision to ensure the accuracy and authenticity of the simulation.

In recent years, digital twin technology has gained significant attention in robotic machining. Zhang et al. [16] Proposed the simulation of welding motions and the optimization of welding processes for robotic systems, aiming to monitor the welding process and enable seamless collaboration with the positioner. However, in contrast to the welding process, robotic milling requires more comprehensive visualization capabilities, such as monitoring machining outcomes and milling forces. Xia et al. [17] introduced a method for monitoring tool wear in robotic milling, validating the stability and effectiveness of both robot trajectory planning and interactive communication. However, actual machining processes require more advanced trajectory planning methods. Calandra et al. [18] demonstrated the ability for two remote users to collaborate in programming a robot by integrating video data streams with robot programming data. However, the proposed data transmission approach is limited by network bandwidth constraints. Zhu et al. [19] employed the Unity3D platform and virtual-real mapping technology to achieve result mapping for robot milling motion simulations and real-time visual monitoring of the milling process. However, this approach does not incorporate tool wear monitoring or other critical processes.

Tool wear prediction, as a critical industrial challenge, has evolved with various solutions over time. Common approaches include physical modeling, traditional machine learning, reinforcement learning, deep learning, and transfer learning. Physical modeling leverages the physical laws of tool wear during the machining process, such as wear rate formulas and thermodynamic models, to guide data analysis. While providing physical interpretability, it is not suitable for complex cutting scenarios [20,21]. Traditional machine learning methods, such as Support Vector Machines (SVM), Random Forest (RF), and Gradient Boosting Decision Trees (GBDT), are used to predict tool wear based on manually extracted features. These methods are characterized by short training times but require effective feature extraction [22,23]. Reinforcement learning frames tool wear prediction as a dynamic decision-making problem, where the agent continuously optimizes decisions through interaction. This approach offers dynamic learning capabilities but requires complex training, either in a simulated or real-world interactive environment [24]. Deep learning utilizes neural networks to process complex time-series data for predicting tool wear, automatically learning data features to enhance prediction accuracy. However, it demands significant computational resources and extensive tuning [25,26]. Transfer learning enables the transfer of knowledge learned from a source task to a target task, reducing the need for target task data, making it especially useful when limited data is available under different working conditions [27,28]. Therefore, transfer learning has been widely applied to the optimization of manufacturing systems due to its ability to leverage historical data, which aligns with the highly variable nature of manufacturing environments [29–31]. In this study, we develop a tool wear prediction algorithm based on the principles of ensemble learning and transfer learning, specifically designed for various operational conditions. This integrated approach combines deep learning, machine learning, and other methods, harnessing the strengths of multiple methods while overcoming the limitations of individual approaches.

In recent years, various methods have been proposed in the field of tool wear monitoring and prediction, some of which combine physical models and data-driven approaches. Sun et al. [32] proposed a physics-informed Gaussian process regression method for tool wear monitoring, while Zhu et al. [33] introduced a physics-informed hidden Markov model (PI-HMM) for tool wear monitoring. By incorporating physical models, these methods enhance the accuracy of predictions; however, they lack automatic feature extraction capabilities and knowledge transfer abilities, leading to limited adaptability and generalization. Additionally, Qin et al. [34] applied autoencoder networks for feature extraction and dimensionality reduction. Gao et al. [35] proposed a multi-source lightweight adaptive replay-based online deep transfer learning algorithm for real-time monitoring. The use of deep transfer learning enables automatic feature extraction and cross-domain learning, but the prediction speed is constrained by the re-training process of deep learning models, and these methods rely on extensive datasets to perform effectively. Huang et al. [36] employed attention mechanisms to enhance the model's focus on important features, while Truong et al. [37] introduced Bayesian regularized artificial neural networks (BRANN) for tool wear prediction. These improvements increased the model's adaptability and stability, but challenges such as high data requirements and computational complexity remain.

In summary, research on the comprehensive monitoring of the robotic milling process remains limited, and several challenges need to be addressed. These include handling multimodal data to achieve a comprehensive and real-time representation of the robot's status, planning robot motion to generate milling trajectories that align with practical production requirements, and designing material removal algorithms to ensure realistic machining outcomes. On the other hand, considering the limitations of existing foundational methods for tool wear prediction, this study proposes a transfer learning algorithm that integrates multiple algorithmic principles. The proposed algorithm combines the automation of deep learning method with the speed of machine learning method, and ensemble learning allows for continuous optimization of predictions while the knowledge transfer process facilitates the integration of historical data, resulting in a comprehensive advantage that individual algorithms cannot provide.

This study adopts the 'virtual-physical integration and virtual control of physical' strategy and proposes an intelligent monitoring system for the robotic milling process based on transfer learning and digital twin. Constructing a digital space for the robot in Unity3D facilitates the exploration of milling simulation technology through dynamic milling algorithm design and the establishment of a motion simulation algorithm. Integrating CNN-LSTM with the two-stage TrAdaBoost.R2 method supports a transfer learning algorithm for effective analysis and prediction of tool wear status, ultimately enhancing milling efficiency and surface quality.

2. Model architecture design

The digital twin system, recognized as an advanced solution, facilitates real-time interaction between the virtual and physical robots through network communication, integrating and synchronizing twin data from both the virtual and physical robots with information and sensing technologies. By leveraging this twin data, the system achieves real-time mapping of robot movements, simulation of the milling process, prediction of tool wear status, optimization of control parameters, and three-dimensional visualization monitoring, ultimately leading to comprehensive management and control of the entire robotic milling operation.

Based on the five-dimensional digital twin model proposed by Professor Tao [38], this paper constructs a five-dimensional architecture of the intelligent monitoring system specifically for the milling process of milling robots, as illustrated in Fig. 1. This architecture primarily comprises five components: the physical layer, the virtual layer, the twin data layer, the application service layer, and the communication connections between these layers.

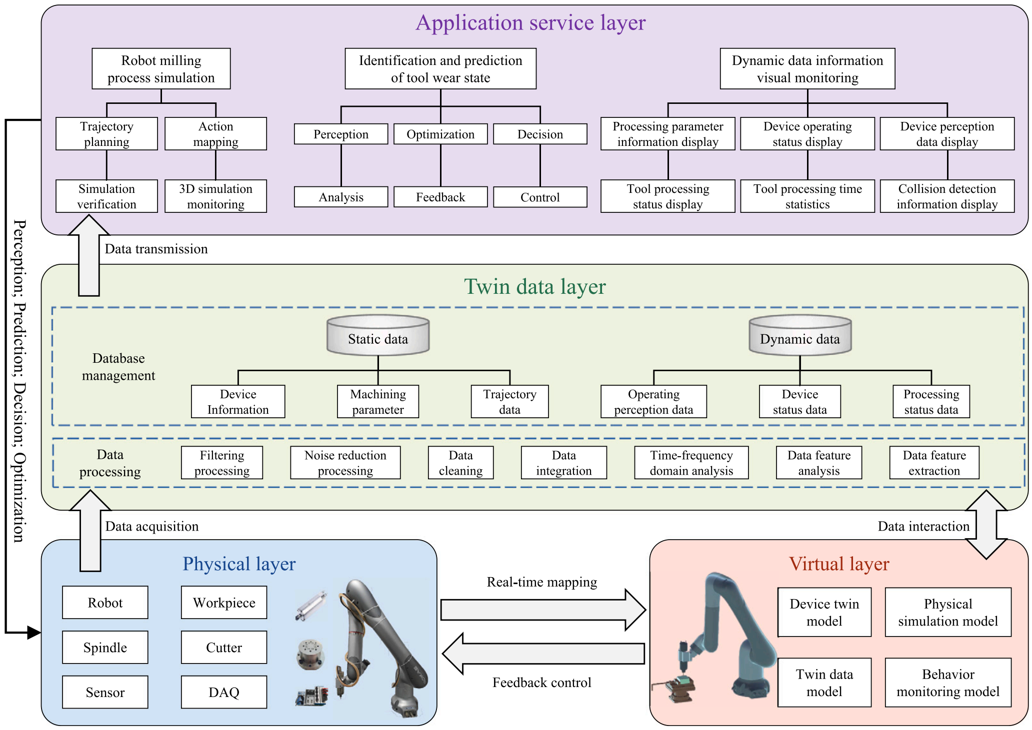

Fig. 1. Five-dimensional architecture for digital twin model of milling robot.

(1) Physical layer
The physical layer of the digital twin system for milling robots primarily consists of the robot arm, electric spindle, controller, frequency converter, sensors, and data acquisition systems. By collecting multisensory and operational data from the physical robot, a virtual representation of the robot is created and driven.

(2) Virtual layer
The virtual layer primarily includes a digital twin model that maps the physical robot in real-time, encompassing its position, shape, material properties, and kinematic features, ultimately facilitating the simulation and monitoring of the entity's operational state. Constructing a digital twin model for a milling robot within the digital twin system involves establishing the physical rules of the robot, creating geometric representation, and developing robotic monitoring scene, as illustrated in Fig. 2. A near-realistic robotic monitoring scenario is created by leveraging the advanced PhysX physics engine embedded in Unity3D, significantly enhancing the authenticity and immersive quality of the simulation environment. The construction of the geometric digital twin model for the milling robot begins with the utilization of SolidWorks software for 3D modeling, producing a model that preserves the same structural and assembly relationships as the physical robot. This model is exported in STL format and imported into 3Ds Max for texture mapping and material rendering, and then saved as an FBX format for import into Unity3D. In Unity3D, the joints are assembled based on their relationships, resulting in a complete virtual robot model. Building upon this foundation, the kinematic principles of the robot are applied to establish the motion relationships between the joints, while constraints such as rotation angles and speeds for each joint are defined to facilitate precise simulation of the robot's physical behaviors.

(3) Twin data layer
Twin data refers to the information that reflects an entity's state and behavior, categorized into static and dynamic data. In the digital twin system, static data includes the robot's geometric shape, dimensions, and spatial relationships, which remain constant after system initialization. In contrast, dynamic data comprises operational information generated during system operation, including temperature, milling force, as well as the angles, velocities, and accelerations of the robot's six axes, reflecting the robot's real-time state. By collecting and processing both types of data, high-precision mapping between virtual and physical entities is achieved. The communication connections and data transmission management between the virtual environment and the physical robotic equipment are illustrated in Fig. 3.
In Unity3D, the digital twin system connects to an SQL Server database by executing specific structured query language (SQL) statements to achieve real-time reception of multi-source heterogeneous data from the physical environment accessed through socket communication. Utilizing the external XCharts plugin in Unity3D, this data is dynamically visualized in the user interface through formats that include line charts and text. Additionally, through the system's API program interface, users can adjust the spindle speed and feed rate to achieve feedback control of the physical robot. This method of data transmission and management facilitates the intuitive display of information regarding the robot's operational status, fault conditions, processing status, and ultimately supports equipment status analysis and informed decision-making.

(4) Application service layer
A digital twin application service platform for milling robots is established within visualization software by integrating the physical layer, virtual layer, and twin data layer. This platform encompasses the simulation of the milling process, prediction of tool wear status, and dynamic data visualization. For the milling process, the system effectively visualizes milling activities, enhances monitoring of the processing state, and enables intelligent equipment management, ultimately optimizing the monitoring and management of the robotic milling process.

(5) Communication connections
Communication connections serve as the bridge among all components. The Socket interface functions as the communication

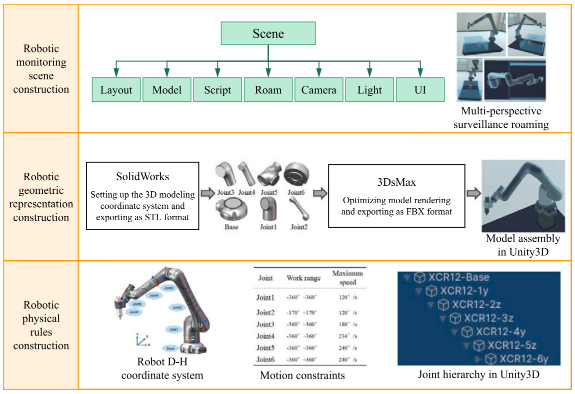

Fig. 2. Digital twin modeling of milling robot.

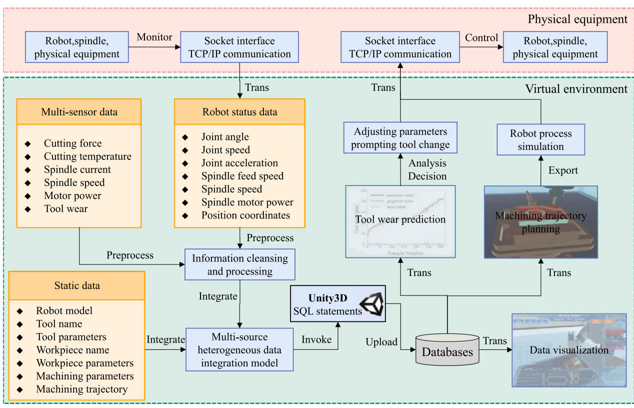

Fig. 3. Communication connection and data transmission management process.

connections layer that resides between the layers, encapsulating the application programming interface (API) of TCP/IP and providing a data channel. This setup enables different applications to exchange information through the socket, facilitating communication interactions. By utilizing these APIs, connection between the physical robot and the virtual environment is established,supporting virtual-physical interaction for robotic devices.

3. Key technologies

3.1. Robotic dynamic milling simulation

The robotic milling process is based on a machining path generated by CAM software, described as NC numerical control codes. These codes are parsed and converted to generate the robot's machining trajectory, which is simulated to achieve realistic and dynamic milling effects.

To achieve a visual simulation of the robot milling process, a material removal algorithm based on mesh deformation is presented. The algorithm utilizes collision detection method to identify the cutting range between the tool and the workpiece, deforming the mesh within this range to simulate the workpiece's deformation during milling. In contrast to conventional material removal algorithm that rely on Boolean operations or swept volume intersections, this approach circumvents complex geometric calculations, reduces computational load, and enhances the real-time performance and quality of visualization in the simulation.

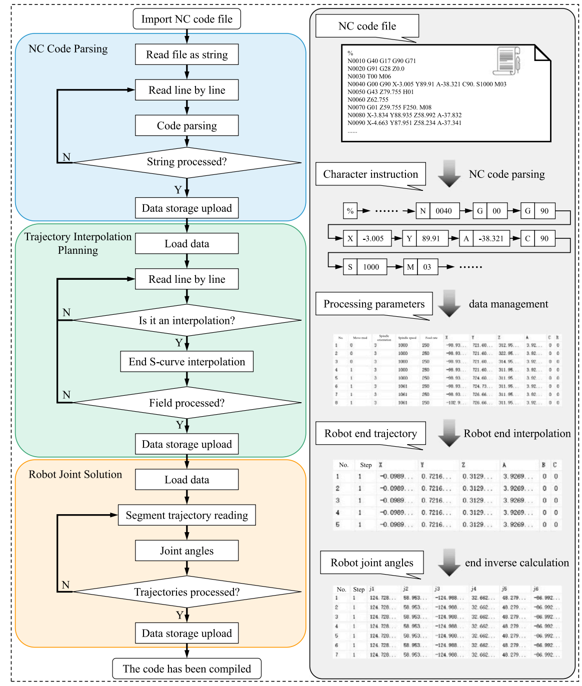

Fig. 4. Robot machining trajectory planning flow.

3.1.1. NC code parsing algorithm design

The NC codes are parsed and converted to guide the robot's machining toolpath trajectory. The process for planning the robot's machining trajectory is illustrated in Fig. 4.

Initially, the NC code file is imported and read as a string for a parsing process involving lexical analysis, syntax analysis, and data compilation. The parsed data is then uploaded to an SQL Server database for storage. Subsequently, the parsed code fields are loaded and read sequentially to perform S-curve interpolation on the interpolation instructions. This step achieves trajectory planning for the robot's end effector, with the resulting interpolated pose data subsequently uploaded. Finally, inverse kinematics calculations are performed on the end-effector poses to determine the corresponding joint angles of the robot. This angle data is stored in the database for future use in driving robot motion simulations, completing the entire NC code compilation process.

3.1.2. Material removal algorithm design

The core of the mesh deformation-based material removal algorithm involves calculating the positional changes of each point in the workpiece mesh under the influence of the tool, reflecting the shape alterations of the workpiece by updating these point positions. Fig. 5(a) illustrates the milling simulation process utilizing mesh deformation.

Initially, the tool is guided to move along a predetermined path. As it approaches the workpiece, this algorithm calculates the distance between the tool's cutting points and the points on the workpiece mesh to determine whether contact occurs. The algorithm then traverses the workpiece mesh, applying deformation processing to the area in contact with the tool. Finally, the workpiece mesh is updated and refreshed to achieve the material removal simulation effect. This algorithm effectively mimics the milling action of the tool on the workpiece, ensuring a high degree of consistency between the simulation results and the actual machining outcomes.

During the milling simulation process, iterating and calculating each workpiece mesh point relative to the milling center of the tool significantly hinders computational efficiency and introduces unnecessary processing time. To optimize this, a spherical bounding box

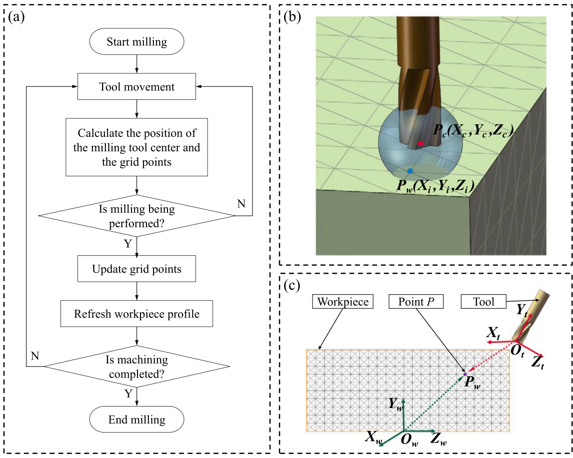

Fig. 5. The schematic of material removal algorithm design. (a) Mesh deformation based material removal algorithm flow. (b) Bounding box for tool. (c) Workpiece grid coordinate transformation diagram.

is introduced around the milling center of the tool. When workpiece mesh points fall within this bounding box, the algorithm assesses their positional relationship with the spherical boundary, as illustrated in Fig. 5(b).

By calculating the three-dimensional spatial distance between a workpiece mesh point $P_w(X_i, Y_i, Z_i)$ and the center of the tool's bounding box $P_C(X_C, Y_C, Z_C)$, the algorithm identifies the mesh points contained within the spherical bounding box. These identified points are then subjected to the material removal algorithm, which updates the workpiece surface to simulate the milling process. This bounding box-based detection method effectively confines the tool's milling range to a specific area, prompting the material removal algorithm to focus on points that require deformation while excluding most others. This significantly enhances the efficiency of both the material removal algorithm and the overall simulation process.

Additionally, achieving comprehensive milling simulation, while considering that the end tool of the six-axis milling robot can rotate at any angle, requires performing coordinate transformations for the workpiece within the tool's coordinate system. When a collision occurs between the workpiece mesh and the tool, the spatial coordinates of the workpiece mesh are first transformed into the tool's coordinate system. Material removal is then executed based on the milling judgment and mesh deformation, after which the workpiece mesh coordinates are restored to their original spatial coordinates for visualization. Fig. 5(c) illustrates the workpiece mesh point P in both the workpiece coordinate system w and the tool coordinate system t.

The workpiece coordinate system w is rotated around the X, Y, and Z axes by angles α, β and γ, respectively, resulting in the following rotation homogeneous transformation matrix:

$$ {}^{t}_{w}\mathrm{Rot}(X,\alpha) = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & \cos\alpha & -\sin\alpha & 0 \\ 0 & \sin\alpha & \cos\alpha & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{1} $$

$$ {}^{t}_{w}\mathrm{Rot}(Y,\beta) = \begin{bmatrix} \cos\beta & 0 & \sin\beta & 0 \\ 0 & 1 & 0 & 0 \\ -\sin\beta & 0 & \cos\beta & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{2} $$

$$ {}^{t}_{w}\mathrm{Rot}(Z,\gamma) = \begin{bmatrix} \cos\gamma & -\sin\gamma & 0 & 0 \\ \sin\gamma & \cos\gamma & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{3} $$

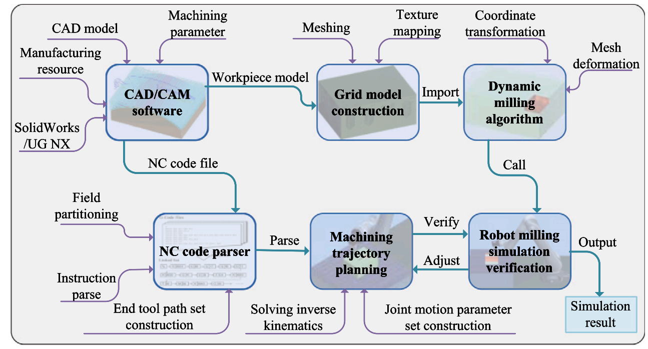

Fig. 6. Dynamic milling simulation flow process.

The workpiece coordinate system w is then translated along the X, Y, and Z directions by distances x, y, and z to obtain the translation homogeneous transformation matrix as follows:

$$ {}^{t}_{w}\mathrm{Trans}(x,y,z) = \begin{bmatrix} 1 & 0 & 0 & x \\ 0 & 1 & 0 & y \\ 0 & 0 & 1 & z \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{4} $$

By combining the rotation matrix and the translation matrix, a general homogeneous transformation matrix is derived as follows:

$$ {}^{t}_{w}T = \begin{bmatrix} \cos\beta\cos\gamma & \cos\gamma\sin\alpha\sin\beta - \cos\alpha\sin\gamma & \sin\alpha\sin\gamma + \cos\alpha\cos\gamma\sin\beta & x \\ \cos\beta\sin\gamma & \cos\alpha\cos\gamma + \sin\alpha\sin\beta\sin\gamma & \cos\alpha\sin\beta\sin\gamma - \cos\gamma\sin\alpha & y \\ -\sin\beta & \cos\beta\sin\alpha & \cos\alpha\cos\beta & z \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{5} $$

By employing this transformation matrix, the coordinates of a mesh point P in the workpiece coordinate system w can be determined in the tool coordinate system t, enabling milling of the workpiece from various tool angles.

3.1.3. Algorithm application

The dynamic milling simulation flow process is illustrated in Fig. 6. First, the workpiece blank is designed in SolidWorks, then meshed and texture-mapped in 3DsMax before being imported into Unity3D as the designated workpiece geometry. A mesh deformation-based material removal algorithm is developed to establish the spatial relationship between the tool and the workpiece through coordinate transformations, enabling an accurate simulation of the material removal effect during milling. Concurrently, an NC code file for the desired part is generated using UG, imported into Unity3D as a string, and parsed according to specified instructions to convert relevant motion commands into end-effector trajectories. Subsequently, the robot's inverse kinematics are applied to derive joint motion parameters based on the end-tool path. Finally, the dynamic milling simulation is engaged for verification and refinement, thereby ensuring the precision and safety of the machining path. In this dynamic milling simulation flow process, the performance and features of the Unity3D platform enable the robot's motion and the virtual milling effects to be presented as a digital twin of the real machining process. Furthermore, the forces, vibrations, and other signals monitored during the milling process can be mapped to each machining step, allowing for real-time monitoring of the process.

3.2. Tool wear prediction

3.2.1. Transfer learning algorithm design

To address the challenges posed by insufficient labeled data stemming from the difficulties in collecting tool wear information and the

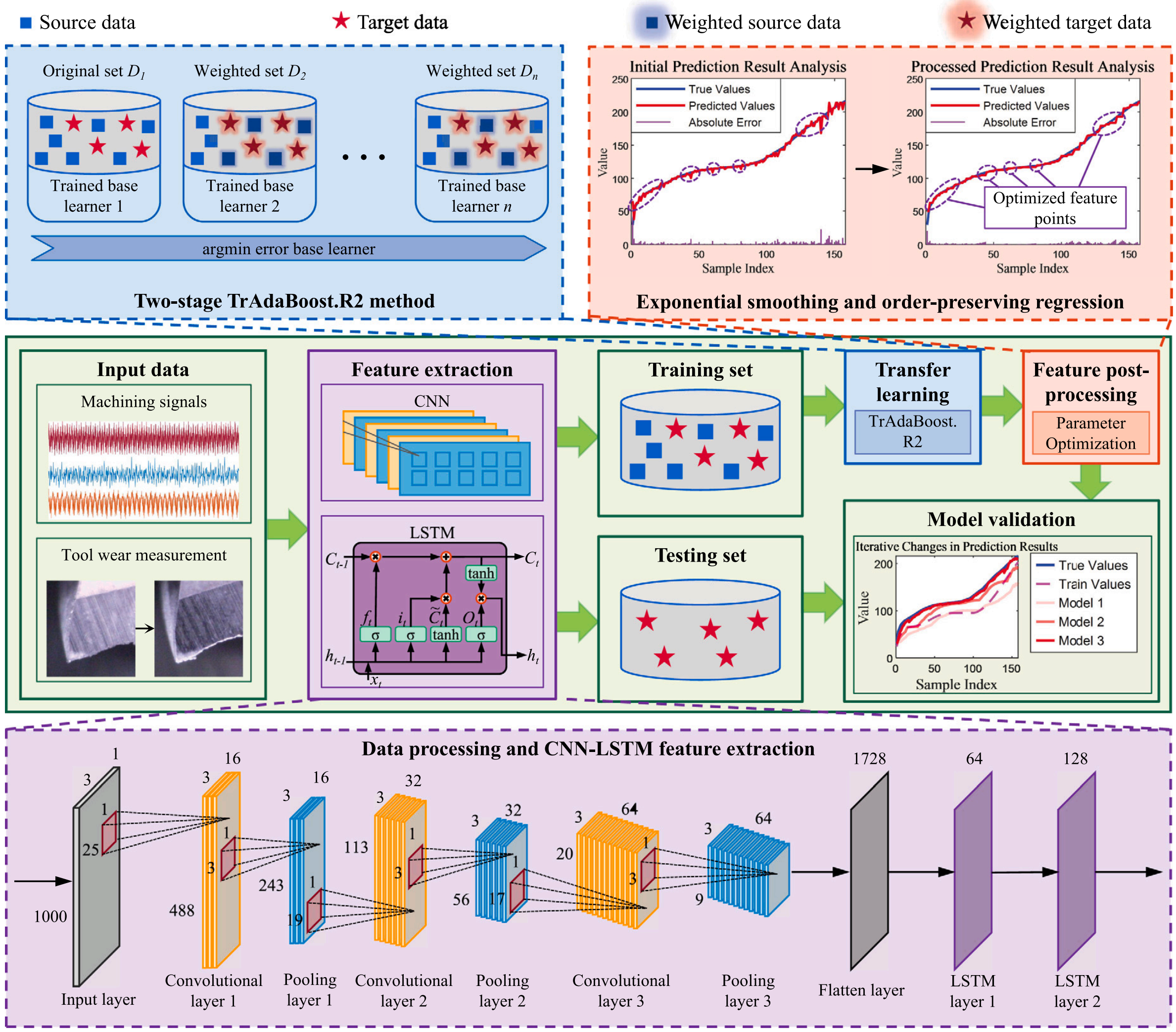

Fig. 7. CNN-LSTM-TrAdaBoost.R2 transfer learning algorithm structure.

issue of non-identically distributed data across various operational conditions, a transfer learning algorithm with automatic feature extraction is proposed to predict tool wear under varying conditions. The overall framework of the developed hybrid algorithm is illustrated in Fig. 7.

Initially, all data undergo feature extraction through a CNN-LSTM deep learning network, which reduces data volume while automatically capturing essential temporal features. The extracted features are divided into a source dataset, comprising historical machining data stored under various conditions in the twin date layer, along with additional labeled datasets, and a target dataset containing current machining condition data. The training set is constructed from the entire source dataset and a portion of the target dataset, making it suitable for transfer learning.

The Two-stage TrAdaBoost.R2 method is employed for instance-based transfer learning, utilizing a weight-updating mechanism to transfer relevant knowledge from the source to the target domain in two stages. This approach enables the algorithm to leverage multi-source, non-identically distributed historical data for accurate predictions of new tasks. Additionally, a post-processing step based on physical laws, including exponential smoothing and isotonic regression, is applied to improve the accuracy of the predicted tool wear values. This step helps mitigate sudden data fluctuations and ensures a smooth, monotonic trend in the prediction curve. The algorithm is subsequently applied to the remaining target dataset for tool wear prediction, demonstrating its transferability and predictive performance.

3.2.2. Algorithm application

Achieving real-time tool wear prediction in Unity3D requires the simultaneous execution of data collection and wear prediction processes, which is accomplished by integrating MATLAB and Unity3D within an interactive development framework. A MATLAB-generated DLL program facilitates real-time signal acquisition and data processing, enabling instantaneous predictions of tool wear status that are subsequently visualized in Unity3D. The entire real-time prediction process for tool wear is illustrated in Fig. 8.

In MATLAB, real-time data acquisition from the NI acquisition card is accomplished by configuring acquisition parameters and establishing an NI session, followed by preprocessing steps such as downsampling and noise filtering. Concurrently, a connection to the twin data layer is established to manage and store the data. Simultaneously, the tool wear prediction algorithm is constructed using historical datasets, employing the CNN-LSTM-TrAdaBoost.R2 method for initial training and transfer learning. The prediction algorithm, along with the necessary MATLAB library files, is then packaged into a DLL file and imported into Unity3D.

In Unity3D, the DLL file is invoked to drive the tool wear prediction algorithm, thereby enabling real-time data collection and dynamic prediction of tool status during machining. This approach facilitates a dynamic display of the tool wear curve, supporting visual analysis of the tool condition. Furthermore, based on real-time prediction, the system can adjust machining parameters, such as spindle speed and

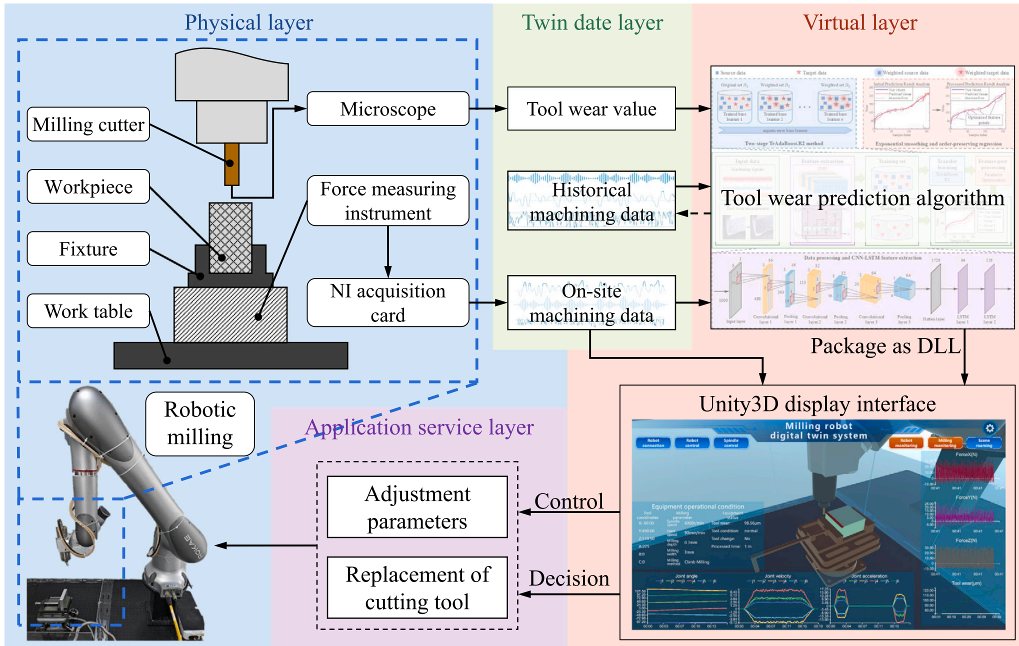

Fig. 8. Real-time tool wear status prediction process.

Table 1
Experimental parameters of the IEEE PHM 2010 dataset.

Parameter	Value	Unit
Spindle speed	10 400	rpm
Feed rate	1555	mm/min
Radial depth	0.125	mm
Axial depth	0.2	mm
Milling method	Climb milling	–
Sampling frequency	50	kHz

feed rate. When the tool wear value exceeds a preset threshold, an alert prompts the operator to replace the tool and halt the machine, effectively mitigating the risk of accidents and losses due to tool wear while enhancing machining efficiency.

4. Experiment and validation

4.1. Verification of tool wear prediction algorithm

Tool wear values, expressed as tool wear width, are critical indicators of the tool's wear condition. Accurate predictions of these values provide direct estimates of specific tool wear, serving as a reference for wear compensation and ultimately improving workpiece quality. In this study, initial experimental data on tool wear is sourced from the IEEE PHM (Prognostics and Health Management) 2010 milling tool wear dataset [39]. The specific processing parameters of the dataset are shown in Table 1. This dataset includes three-axis milling forces and tool wear values for three different milling cutters, referred to as C1, C4, and C6, with each cutter having 315 instances of milling force data. For each instance, the average wear value across the three cutting edges is used as the data label.

Each milling force data sample contains approximately 200,000 time-series data points. To streamline subsequent processing and training of the transfer learning algorithm, the milling force signal is preprocessed by isolating the stable middle 100,000 data points from each sample. These data points are then downsampled through averaging to yield a final sample comprising 1000 data points.

4.1.1. Ablation experiment

To evaluate the performance of the proposed method, an ablation study was conducted on the dataset, comparing four distinct approaches. data from the C1 and C4 milling cutters were utilized as source domain data, while data from the C6 milling cutter served as the target domain :

- TrAdaBoost.R2: This method employs the Two-stage TrAdaBoost.R2 method for regression, where feature extraction is achieved by averaging the cutting forces in each direction from the original dataset, thereby simplifying the input.
- CNN-TrAdaBoost.R2: This approach utilizes a Convolutional Neural Network (CNN) for feature extraction, combined with the two-stage TrAdaBoost.R2 method for regression. In this configuration, the LSTM layer is replaced with a flattening layer to streamline the algorithm.
- CNN-LSTM: This method applies a CNN-LSTM architecture for feature extraction, utilizing pre-trained source data. Regression is performed through two fully connected layers, culminating in a regression output layer.
- CNN-LSTM-TrAdaBoost.R2: This proposed hybrid method integrates CNN-LSTM for feature extraction with the two-stage TrAdaBoost.R2 method for regression, with the aim of enhancing prediction accuracy and robustness.

Table 2 presents the initial and processed data errors for the four methods described above, while the fitted curves are illustrated in Fig. 9. The comparison metrics employed include Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the coefficient of determination (R^2).

The proposed method demonstrates superior performance in terms of MAE, RMSE, and R^2 values compared to the other three methods. With the incorporation of post-processing techniques including exponential smoothing and isotonic regression, the MAE and RMSE of all four prediction methods are reduced, and R^2 shows improvement, indicating that post-processing can enhance the predictive accuracy of the methods. Among these metrics, R^2 is selected as the representative measure for evaluating accuracy enhancement. The results indicate that the proposed method achieves the highest R^2, reflecting improvements

Table 2
Comparison of ablation experiment results.

Method	Initial			Processed		
	MAE	RMSE	R^2	MAE	RMSE	R^2
TrAdaBoost.R2	7.6738	10.4389	0.9332	5.3740	7.0644	0.9694
CNN-TrAdaBoost.R2	4.4312	7.3072	0.9673	3.1172	5.4106	0.9821
CNN-LSTM	2.9697	4.0027	0.9899	2.1543	2.8957	0.9947
CNN-LSTM-TrAdaBoost.R2	**2.1393**	**3.8261**	**0.9910**	**1.5870**	**2.3815**	**0.9965**

of 6.19%, 2.45%, and 0.11% over TrAdaBoost.R2, CNN-TrAdaBoost.R2, and CNN-LSTM, respectively.

Firstly, the models of TrAdaBoost.R2, CNN-TrAdaBoost .R2, and CNN-LSTM-TrAdaBoost.R2 differ in the feature extraction methods employed. Specifically, TrAdaBoost.R2 does not perform feature extraction, CNN-TrAdaBoost.R2 utilizes a CNN for feature extraction, and CNN-LSTM-TrAdaBoost.R2 incorporates a CNN-LSTM network for feature extraction. These differences highlight the substantial impact of the feature extraction process on the accuracy of prediction results. This suggests that automatic feature extraction, leveraging both forward and backward memory, enables the model to focus on meaningful features, reduces noise interference, and improves the stability of its predictions.

Secondly, the distinction between the CNN-LSTM and CNN-LSTM-TrAdaBoost.R2 models lies in the transfer learning methods employed. CNN-LSTM uses a model-parameter-based transfer learning method, while CNN-LSTM-TrAdaBoost.R2 applies an instance-based transfer learning method. This contrast underscores the influence of different transfer learning methods on prediction accuracy, demonstrating that instance-based transfer learning enables the model to more effectively leverage knowledge from the source domain, resulting in improved predictions for the target domain. The instance weight update mechanism during the iterative process allows the model to place greater emphasis on the target data, thereby enhancing the reliability of its predictions. Moreover, the instance-based transfer learning method offers a significant advantage in training speed over CNN-LSTM with retraining, making it more suitable for real-time tool wear prediction.

In summary, by integrating various key techniques, the CNN-LSTM-TrAdaBoost.R2 model demonstrates exceptional performance and efficiency.

4.1.2. Dataset verification

This section focuses on dataset validation and experimental data verification. Initially, data from the C1 and C4 milling cutters were used as source domain data, while data from the C6 milling cutter served as the target domain within the previously discussed CNN-LSTM-TrAdaBoost.R2 transfer learning algorithm. RMSE, MAE, and R^2 were employed to evaluate the performance of the regression algorithms. The test results, shown in Fig. 10(a), indicate an R^2 of 0.9910 for tool wear predictions on the external dataset, which improved to 0.9965 after post-processing, demonstrating robust predictive performance.

Building on these findings, on-site machining data were collected from the constructed milling robot machining experimental platform to form the experimental dataset, leveraging the external dataset as historical data for transfer learning applications aimed at predicting tool wear under new operating conditions. The milling robot machining platform utilized the robot (ROKAE-CR12) for milling, and the tool used was a 6 mm diameter tungsten carbide three-flute flat-end mill (UA100-S3-06016). The workpiece material was aluminum alloy AL6061, with dimensions of 20 mm × 100 mm × 100 mm. Milling force signals in three directions during the milling operation were measured using a strain-based four-component force sensor (HR-F3108). Signal collection was performed with a data acquisition card (NI-9215). Tool wear values were calibrated using a microscope (Dino-Lite-AM7915). The specific experimental parameters for the milling operation are shown in Table 3.

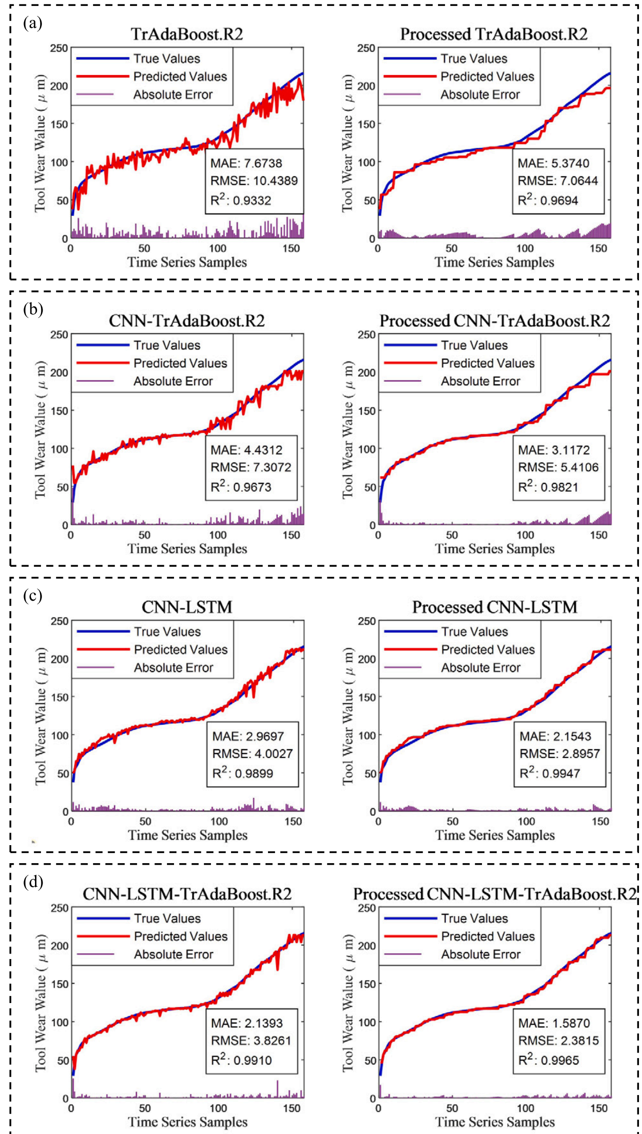

Fig. 9. Results of ablation experiment. (a) TrAdaBoost.R2. (b) CNN-TrAdaBoost.R2. (c) CNN-LSTM. (d) CNN-LSTM-TrAdaBoost.R2.

Table 3
Experimental parameters of on-site machining.

Parameter	Value	Unit
Spindle speed	6000	r/min
Feed rate	90	mm/min
Radial depth	0.3	mm
Axial depth	3	mm
Milling method	Climb milling	–
Sampling frequency	10	kHz

Based on the aforementioned tool wear experiment, a total of 140 sets of tool wear data and three-directional milling force signals were collected. During each measurement, the wear values of the three cutting edges of the milling tool were recorded, and the average value was calculated to serve as the label for the tool wear dataset. The test results for the experimental dataset, presented in Fig. 10(b), show an R^2 of 0.9324 for tool wear prediction, with a post-processing result of 0.9776. The predictive performance experienced a slight decline compared to the results from the external dataset. This discrepancy can be attributed to the different data acquisition conditions between the

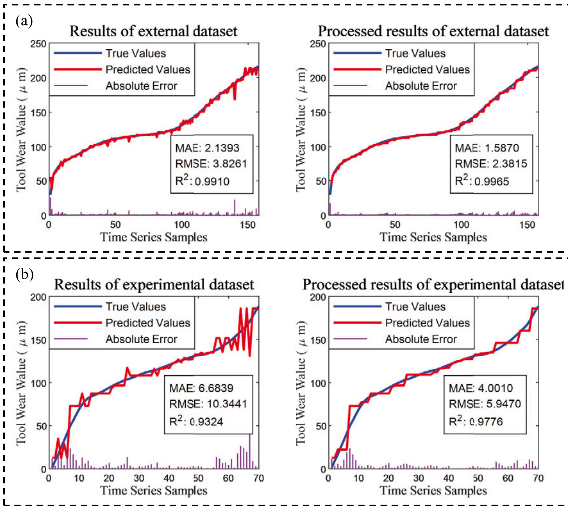

Fig. 10. Results of dataset verification. (a) External dataset. (b) Experimental dataset.

Table 4
Comparison of MAE and RMSE among existing models.

Method	MAE	RMSE
FFCA-PCWN [40]	3.52	4.90
Re-BLSTM [41]	2.63	4.81
ConvLSTM-ATT [42]	4.06	5.72
SSAE-BP [43]	7.29	10.08
CNN-LSTM-TrAdaBoost.R2	**2.14**	**3.83**

on-site machining data and the external dataset, indicating that data quality has a significant impact on prediction accuracy. The lower data quality is reflected in greater noise and insufficient wear data in the later stages, leading to higher fluctuations in the prediction results and inaccurate predictions for the tool wear at the final stage.

Although that, the algorithm still provides accurate and reliable overall trend predictions for tool wear, effectively meeting the requirements for on-site machining. These experimental results demonstrate that the proposed method can achieve superior tool wear prediction under cross-dataset conditions.

4.1.3. Comparison with existing models

In order to further investigate the performance of the proposed CNN-LSTM-TrAdaBoost.R2 model in predicting tool wear, it is compared with several existing models, including FFCA+PCWN [40], Re-BLSTM [41], ConvLSTM-ATT [42], and SSAE-BP [43]. The prediction results for all models are based on the C6 milling cutter data from the IEEE PHM 2010 dataset, without the use of post-processing. The evaluation metrics are presented in Table 4

Compared to existing tool wear prediction methods, the proposed CNN-LSTM-TrAdaBoost.R2 model demonstrates a substantial reduction in MAE and RMSE, showcasing superior performance in terms of both prediction accuracy and adaptability. While advanced methods such as FFCA+PCWN, Re-BLSTM, ConvLSTM-ATT, and SSAE-BP each offer certain strengths in feature extraction and physical modeling, they encounter challenges such as dependence on large amounts of labeled data, limited transfer learning capabilities, high model complexity, and significant computational costs. In contrast, the CNN-LSTM-TrAdaBoost.R2 model proposed in this study integrates the CNN-LSTM method for temporal feature extraction with TrAdaBoost.R2 to enhance transfer learning, addressing issues related to excessive data requirements and overfitting while maintaining high prediction accuracy, even in data-limited scenarios. Furthermore, this approach overcomes the limitations of traditional deep learning models, particularly in handling diverse tool types and operating conditions, demonstrating stronger generalization and adaptability. As a result, the CNN-LSTM-TrAdaBoost.R2 model exhibits superior performance in tool wear prediction, particularly in scenarios with limited data and variable conditions.

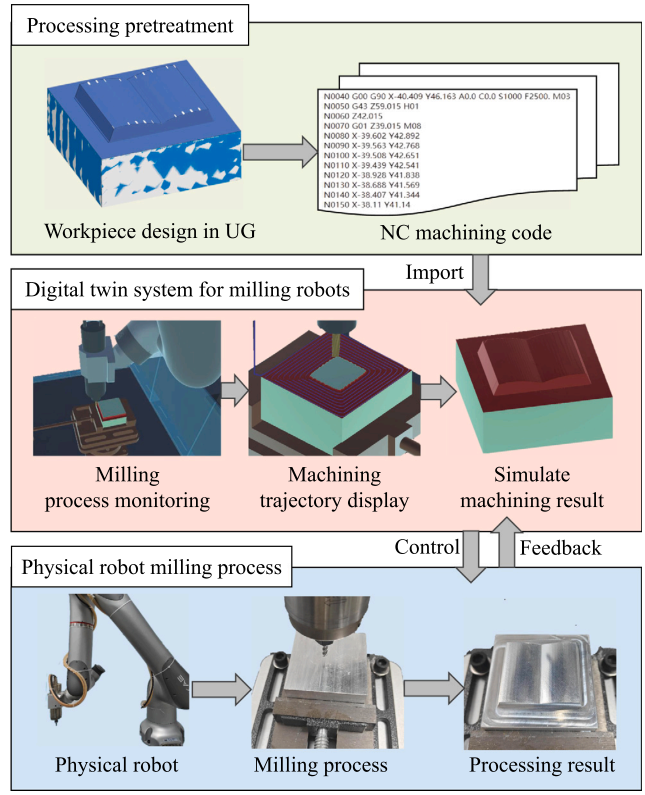

Fig. 11. Milling robot virtual-real interaction flow.

4.2. Verification of visualization monitoring

The robotic milling simulation within the digital twin system imports NC code files and translates them into motion commands for virtual milling operations. To validate the accuracy and practicality of this functionality, pre-designed NC codes were used in experimental tests, enabling the virtual and physical robots to perform milling operations on a workpiece blank along a predetermined path simultaneously, as illustrated in Fig. 11.

The three-dimensional visualization interface of the digital twin system for the milling robot integrates various components, including text boxes, graphs, scenes, and the milling robot model, as shown in Fig. 12. This Unity3D interface displays dynamically presented information such as the robot's joint motion parameters, equipment operating status, milling force signals, and tool wear predictions, which are acquired from sensor signals and the prediction algorithm. By continuously updating the charts, the system performs statistical and analytical processing of various data, enabling effective monitoring of the robot's operating status and milling progress.

Experimental results demonstrate that the proposed digital twin system facilitates virtual-real interaction, enabling seamless simulation and 3D visualization of the milling process, with a stable refresh rate consistently above 30 FPS while effectively visualizing the material removal process. The results confirm that the digital twin system offers realistic scene designing, exceptional 3D visualization effects, smooth

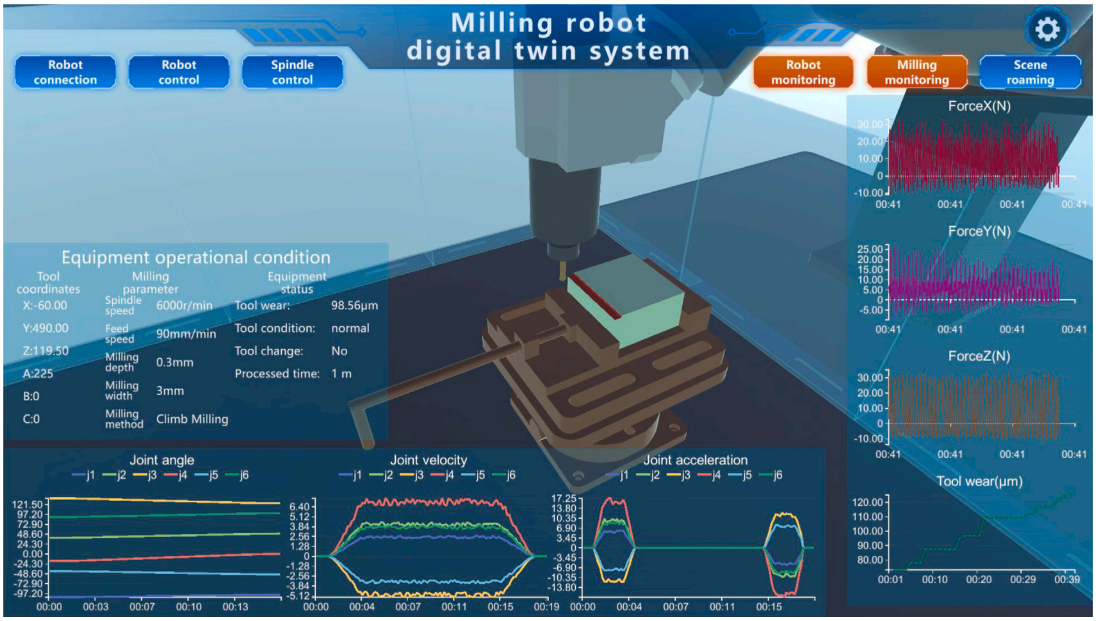

Fig. 12. Digital twin 3D visualization monitoring interface.

motion simulation, and low data collection and transmission delay, allowing for effective 3D visualization monitoring of the physical milling process.

5. Conclusion

This study addresses the increasing demands for intelligence and digitalization in milling robots by proposing a digital twin-based system for milling process simulation and tool wear prediction. This innovative system leverages Unity3D and modern communication technologies to effectively simulate material removal during milling operations and monitor tool wear status in real-time. Additionally, it employs a CNN-LSTM architecture for automatic feature extraction and introduces a Two-stage TrAdaBoost. R2 method for transfer learning.

The experimental results demonstrate that:

(a) The system maintains a refresh rate exceeding 30 FPS during operation, ensuring effective real-time monitoring of the environment and control of the robot.
(b) The proposed method, which integrates deep learning method with the Two-stage TrAdaBoost.R2 method, achieves a prediction coefficient (R^2) of 0.9910 for dataset predictions, offering a valuable methodological reference for tool wear prediction algorithms across various operational conditions.

This paper primarily focuses on the construction and functional integration of the digital twin system for milling robots, elaborating on the key technologies underlying digital twin and emphasizing algorithm for tool wear prediction. However, the robot monitoring system presented in this study still has limitations in fully monitoring the milling process. To address the issue of insufficient monitoring of machining data during the process, virtual cutting forces can be predicted by calculating the tool-workpiece intersection area in real time. To address the problem of monitoring the surface quality after machining, improving the accuracy of the proposed material removal algorithm can help simulate residual material and predict the surface quality. Additionally, the transfer learning algorithm proposed in this study still has room for improvement in transfer efficiency. To address the problem of insufficient source data collection in the early stages of machining, data augmentation can be achieved through model simulation and adversarial training to increase the amount of data. To address the issue of heterogeneous transfer caused by different source data conditions, feature mapping methods can be used to reduce the differences between source data, thus enabling domain adaptation.

CRediT authorship contribution statement

Zhaoju Zhu: Writing – review & editing, Supervision, Resources, Project administration, Methodology, Funding acquisition, Data curation, Conceptualization. **Wenrong Zhu:** Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Jianwei Huang:** Writing – review & editing, Software, Formal analysis, Data curation. **Bingwei He:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition, Formal analysis, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used ChatGPT in order to improve readability and language. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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